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Spatial and temporal stability of weed populations over five years

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The size, location, and variation in time of weed patches within an arable field were analyzed with the ultimate goal of simplifying weed mapping. Annual and perennial weeds were sampled yearly from 1993 to 1997 at 410 permanent grid points in a 1.3-ha no-till field sown to row crops each year. Geostatistical techniques were used to examine the data as follows: (1) spatial structure within years; (2) relationships of spatial structure to literature-derived population parameters, such as seed production and seed longevity; and (3) stability of weed patches across years. Within years, densities were more variable across crop rows and patches were elongated along rows. Aggregation of seedlings into patches was strongest for annuals and, more generally, for species whose seeds were dispersed by combine harvesting. Patches were most persistent for perennials and, more generally, for species whose seeds dispersed prior to expected dates of combine harvesting. For the most abundant weed in the field, the annual, *Setaria viridis*, locations of patches in the current year could be used to predict patch locations in the following year, but not thereafter.

Nomenclature: *Amaranthus retroflexus* L. AMARE, redroot pigweed; *Asclepias syriaca* L. ASCSY, common milkweed; *Brassica kaber* (DC.) L.C. Wheeler SINAR, wild mustard; *Chenopodium album* L. CHEAL, common lambsquarters; *Cirsium arvense* (L.) Scop CIRAR, Canada thistle; *Elytrigia repens* (L.) Nevski AGRRE, quackgrass; *Setaria viridis* (L.) Beauv. SETVI, green foxtail; *Glycine max* (L.) Merr., soybean.

Key words: Cross-semivariogram, geostatistics, kriging, patch, precision farming, semivariogram.

Weeds occur in patches (Bigwood and Inouye 1988; van Groenendael 1988; Halstead et al. 1990; Johnson et al. 1995; Marshal 1988; Mortensen et al. 1993; Nordmeyer and Niemann 1992; Thornton et al. 1990; Wiles et al. 1992) because they tend to cluster where conditions such as nutrient and soil moisture are favorable, because of persistent propagule banks and because seed dispersal is often limited to short distances (Streibig et al. 1984; Thornton et al. 1990). However, this has been disregarded in agricultural practice, where the decision to apply herbicides generally is based on average weed pressure. Similarly, in weed research, most demographic weed models describe mean changes in time and assume uniform distributions in the field.

As the social and scientific paradigms change, spatial variability should be perceived as critical to understanding weed population dynamics (Kareiva 1990). Indeed, the effect of spatial variability is thought to be so important that some weed scientists (Ghersa and Roush 1993; Maxwell and Ghersa 1992) suggest it may be more profitable to pursue strategies aimed at managing dispersal and distribution of weed propagules than to concentrate efforts on weed/crop interactions.

Knowledge of spatial variability is required to increase weed management efficiency (Moloney 1988; Wiles et al. 1992a; Wilson et al. 1985; Wilson and Brain 1990). Currently, yield loss is usually overestimated (Auld and Tisdell 1987, 1988; Brain and Cousens 1990; Dent et al. 1989; Thornton et al. 1990) because of the patchiness of weeds. Consequently, the need for control measures may not be evaluated correctly (Wiles et al. 1992b). The inability or unwillingness to adapt herbicide treatments to weed patchiness is a source of inefficiency in weed control (Thompson 1986; Thornton et al. 1990; Wiles et al. 1992b; Wilson and Brain 1991) and may encourage overuse of herbicides (Dent et al. 1989).

Currently, seedling maps are still the most practical approach to target management efforts (Cardina et al. 1996). Unfortunately, spatial variability is a mapping problem for researchers and farmers because patchiness decreases the accuracy of density estimates, thus increasing the number of samples necessary to estimate the infestation (Wiles et al. 1993). Because samples obtained close to one another vary less than samples obtained at larger distances (Legendre and Fortin 1989; Lybecker et al. 1991), knowledge about spatial correlation is needed to develop unbiased and accurate sample plans (Cardina et al. 1995).

Methods such as the negative binomial (Doyle 1991; Hughes 1990; Mortensen et al. 1993; Wiles et al. 1992b), mean/variance ratio (Lloyd 1967; Ludwig and Reynolds 1988), or Lloyd's mean crowding index (Wiles et al. 1992a) provide nonspatial descriptions of how weeds are distributed. However, they cannot be used to estimate the density, location, or arrangement of weeds (Mortensen et al. 1993). Therefore, alternative analytical methods that rely on the geographic location of samples must be used to draw accurate inferences about spatial arrangement. Geostatistical techniques offer an alternative approach (Johnson et al. 1996) and have already been used to study weed seed banks (Cardina et al. 1996; Halstead et al. 1990) and emerged plant populations (Cardina et al. 1995, 1996; Gerhards et al. 1996; Johnson et al. 1996; Mortensen et al. 1993). In these studies, weed distributions of various fields were com-

TABLE 1. Mean seedling density and standard deviation for the seven most frequently occurring species during 4 yr in a no-till *Glycine max* field at the Swan Lake Research Farm, Morris, MN.

Species	1993		1994		1996		1997	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	plants m^{-2}							
Amaranthus retroflexus	10.5	19.8	1.4	5.7	0.7	2.9	0.4	4.7
Asclepias syriaca	0.0	0.0	0.3	2.3	0.9	4.8	1.6	7.4
Brassica kaber	0.8	3.0	0.5	3.4	0.0	0.0	0.0	0.0
Chenopodium album	2.7	10.2	1.0	6.4	1.1	4.8	0.1	1.2
Cirsium arvense	4.6	13.0	8.6	22.6	2.2	8.1	2.2	8.3
Elytrigia repens	4.6	42.9	0.0	0.0	0.0	0.0	5.3	25.7
Setaria viridis	151.2	490.0	40.7	120.1	98.3	229.7	11.3	24.2

pared, or seedbanks and seedlings of a given field were related.

Comparisons of spatial variability among different species may help to identify the mechanisms that cause patchiness and to make extrapolations to similar but unstudied species, but such comparisons have not yet been made. Likewise, the stability and spatial structure of populations over several years, which is essential to understand and predict patch development through time, has not yet been studied extensively. Consequently, the objectives of this study were to: (1) describe spatial structure and its development over time for various weed species coexisting in a single field, (2) relate the observed spatial variability to biological characteristics of the species, and (3) use this knowledge to predict the location of the following years' weed patches in the same field and evaluate the usefulness of the resulting weed maps for site-specific herbicide spraying.

Materials and Methods

Data Collection

A field survey of weed seedling populations was conducted from 1993 to 1997 at the Swan Lake Research Farm, Stevens County, MN. The field was 54 m wide (east–west) and 244 m long (north–south). A distinct semicircular depression (5-m elevation difference) existed near the middle of the eastern edge of the field. The depression served as the drainage outlet for runoff from the entire field. Soils were a mixture of four series (Lewis et al. 1971). Ranging from sandy upland to clay-rich lowland, these soils were Sverdrup sandy loam (Udic Haploboroll, coarse-loamy, mixed); Barnes loam (Udic Haploboroll, fine-loamy, mixed); Aastad clay loam (Pachic Udic Haploboroll, fine-loamy, mixed); and Flom silty clay loam (Typic Haplaquoll, fine-loamy, mixed, noncalcareous, frigid).

Each year in mid-May, the field was planted in *Glycine max* at 30 seeds m^{-2} using a commercially available no-till planter. Rows were spaced 0.76 m apart and oriented north to south. Fertilizer (13-13-13 N-P-K) was broadcast before sowing at 100 kg ha^{-1}. Weeds were controlled with postemergence herbicides and cultivation. Postemergence applications included bentazon at 0.8 kg ai ha^{-1} each year, and imazethapyr at 0.07 kg ai ha^{-1} (plus additives according to label instructions) in all years except 1996. Two weeks after postemergence applications, an interrow cultivation was performed. An additional application of 1.1 kg ai ha^{-1} glyphosate was used to control perennial weeds, either before planting or after harvest.

Weed seedlings were identified and counted in 0.1-m^2 quadrats once each year (except in 1995) prior to postemergence applications (approximately June 14 to 18). Weed density by species was obtained at the same locations each year. Beginning at the field margins, samples were taken on a regular sampling grid with 10 rows and 41 columns. Distances between grid points were 6.1 m in both the x and y directions, except between the last two sample rows, which were separated by 3.05 m. Seven species were identified and analyzed in detail. These included *Amaranthus retroflexus, Asclepias syriaca, Brassica kaber, Chenopodium album, Cirsium arvense, Elytrigia repens,* and *Setaria viridis.*

Data Analysis

Summary statistics (mean, variance, and skewness) were calculated for each weed species (Table 1). Because weed density data were positively skewed (a large proportion of quadrats contained no seedlings), $\log(z + 1)$ transformation was used in subsequent analysis. Large-scale trends and independence of means and variances were examined according to Hamlett et al. (1986).

Empirical semivariograms. Within each year, spatial correlation between data points was analyzed using the semivariance statistic

$$\gamma_h = \frac{1}{2 \cdot N_h} \sum (z_{i+h} - z_i)^2, \qquad [1]$$

where γ_h is the empirical semivariance for the distance h, N_h is the number of points separated by the distance h, and z_i is the weed density at location i. This statistic is then plotted for each separation distance h (termed an empirical semivariogram) and characterizes the spatial variability of weed densities as a function of distance between locations. Separate empirical semivariograms were established in two directions: along the rows (i.e., 0°, or the north–south direction) and across the rows (i.e., 90°, or the east–west direction). Semivariograms were plotted for each species and each year.

Cross-semivariograms were used to study the spatial variability in weed density between two different years using the equation

$$\gamma_h = \frac{1}{2 \cdot N_h} \sum (z_{i+h,j} - z_{i,j})(z_{i+h,j+t} - z_{i,j+t}), \qquad [2]$$

where $z_{i,j}$ was the weed density of a given species at location i for year j, and t was the number of years between the first and second observation years. The correlation between seedling densities across 2 yr also was calculated using the equation

$$\rho_h = \frac{1 - \gamma_h}{\sigma_j \sigma_{j+t}}, \qquad [3]$$

where ρ_h is the autocorrelation and σ_j and σ_{j+t} are the respective population standard deviations for 2 yr.

Fitting models to semivariograms. To quantitatively describe the spatial structure of a given weed population, a nested spherical model was fit to both empirical semivariograms and cross-semivariograms.

Model 1:

$$\begin{cases} \text{if } h < a_1 & \gamma_1(h) = c_1 \cdot \left[1.5 \cdot \dfrac{h}{a_1} - 0.5 \cdot \left(\dfrac{h}{a_1}\right)^3\right] \\ \text{if } h \geq a_1 & \gamma_1(h) = c_1 \end{cases} \qquad [4]$$

Model 2:

$$\begin{cases} \text{if } h < a_2 & \gamma_2(h) = c_2 \cdot \left[1.5 \cdot \dfrac{h}{a_2} - 0.5 \cdot \left(\dfrac{h}{a_2}\right)^3\right] \\ \text{if } h \geq a_2 & \gamma_2(h) = c_2 \end{cases} \qquad [5]$$

Total model: $$\gamma(h) = c_0 + \gamma_1(h) + \gamma_2(h) \qquad [6]$$

c_o is the nugget (representing small-scale variation that cannot be described with the present sampling scheme), c_1 and c_2 are the contributions of the first and second spatial structures to the total variance (sill), and a_1 and a_2 are the ranges (with different values for the 0° and 90° directions). This model was fit to the empirical semivariogram for each species and year using an iterative least-squares procedure. Points with fewer than 50 pairs were excluded because they were considered unreliable (Cressie 1991; Hamlett et al. 1986; Journel and Huijbregts 1978). Values for the ranges (a_1, a_2), contributions (c_1, c_2), and nugget (c_0) were estimated using weighted least-squares based on number of pairs, N_h.

Analyses of the semivariogram parameters. To relate the observed spatial variability of weed populations to biological characteristics of that species, a linear model was used to estimate changes in the nugget, ranges, contributions of species characteristics (density, habit, seed production, or germination rate), and year. This general model is

$$\begin{aligned} \text{Output variable} &= \text{constant} + \text{year efffect} \\ &\quad + \text{species effect} + \text{error} \end{aligned} \qquad [7]$$

where the output variable represents one of the model parameters (nugget, ranges, contributions) or the values of ρ_h for distance $h = 0$, that is, the correlation between the seedling densities of two different years.

To relate the effect of species characteristics to changes in spatial variability, a series of auxiliary variables were incorporated in the model in Equation 7. Model I studied the influence of plant densities using the mean number of plants per square meter observed for each species and year, as well as the annual or perennial character ("habit" in botanical terminology) of the species.

$$\begin{aligned} \text{Output variable} &= \text{constant} + \text{year effect} \\ &\quad + \text{growth habit effect} \\ &\quad + \alpha \times \text{mean density} + \text{error} \end{aligned} \qquad [8]$$

α is the parameter associated with the covariate "mean plant density" calculated for each year and species. In the case of parameters describing cross-semivariograms, two different variables were used: mean densities of year j and year $j + t$.

Model II was developed for annuals, only, to study the effect of pre- and postharvest seed production on spatial variability such that

$$\begin{aligned} &\text{Output variable} \\ &\quad = \text{constant} + \text{year effect} \\ &\qquad + \beta \times \text{numbers of seeds dispersed before harvest} \\ &\qquad + \chi \times \text{numbers of seeds dispersed during harvest} \\ &\qquad + \text{error} \end{aligned} \qquad [9]$$

where β and χ are the parameters associated to the covariates "seeds dispersed before harvest" and "seeds dispersed after harvest," respectively. Seed production data were not collected during the field trials but were adapted from the means of the two values reported by Forcella et al. (1996) for seed production by annual species.

Model III studied the effect of germination rate on spatial variability, as shown in the following equation.

$$\begin{aligned} \text{Output variable} &= \text{constant} + \text{year effect} \\ &\quad + \text{growth habit effect} \\ &\quad + \delta \times b_1 + \phi \times b_2 + \text{error} \end{aligned} \qquad [10]$$

δ and ϕ are the parameters associated with the covariates b_1 and b_2, respectively. The values of b_1 and b_2 were taken from Burnside et al. (1996), who used the equation

$$\ln \frac{y}{1 - y} = b_1 + b_2 \times (\text{length of seed burial [in years]}), \qquad [11]$$

where y is the percentage of germinating seeds.

Seed production and germination could not be studied in the same model because data were not available for all species. The habit effect was not included in the second model (Equation 9) because this model was applied solely to annuals. The final models contained only those input variables that were significant ($P = 0.01$).

Interpolation using ordinary kriging and cokriging. Kriging was used to provide estimates of weed seedling density by species and year at unsampled locations across the field. Kriging is an interpolation technique that estimates the value of an attribute, z, at unsampled locations in the field based on available data at neighboring locations and semivariogram model parameters. Cokriging provides estimates of a sparsely sampled variable, z', based on available data, and an extensively sampled variable, z, as well as the semivariograms of the variables z and z' and their cross-semivariogram. In this paper, cokriging was used in a slightly unorthodox manner. The aim was to test whether cokriging could use the sampled data of year j to predict the weed distribution of year $j + t$. If we wish to predict the weed distribution at time $j + t$, neither the semivariogram of year

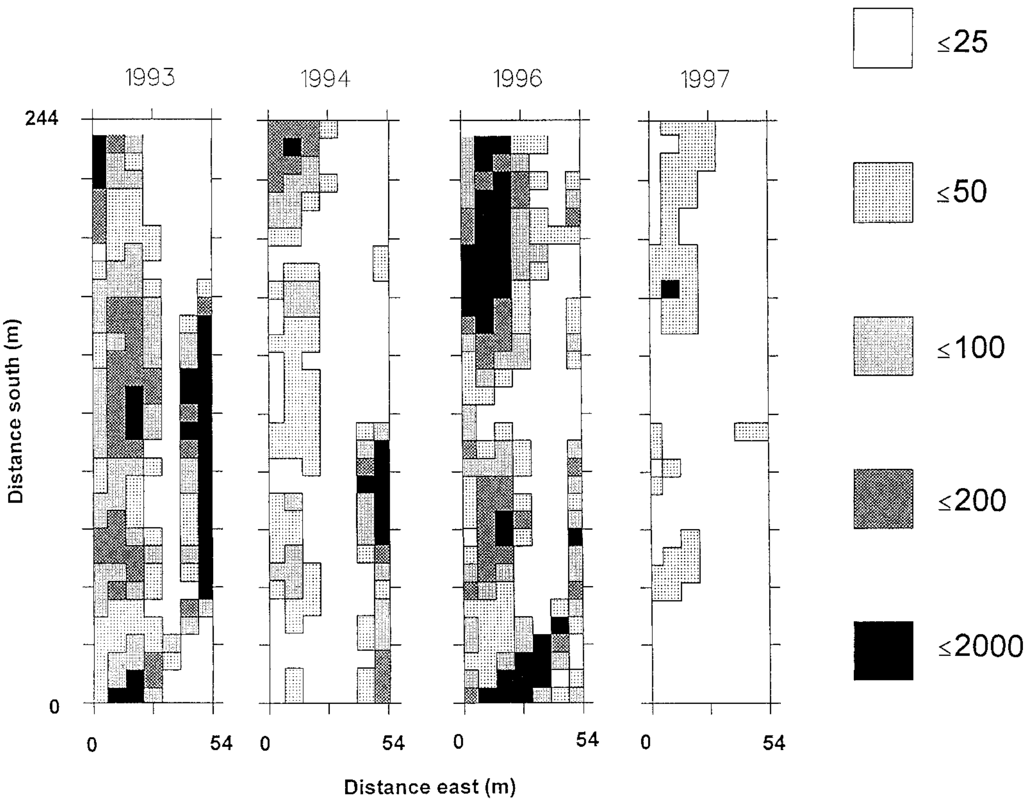

FIGURE 1. Distributions and density (plants m^{-2}) ranges of *Setaria viridis* in the same field in 1993, 1994, 1996, and 1997. Maps were generated using density data from quadrats set on a 6.1-m grid system.

$j + t$ nor the cross-semivariogram for years j and $j + t$ would be known in advance. Therefore, the semivariogram of year j was also used for year $j + t$, and the cross-semivariogram was the mean from the cross-semivariograms of all pairs of years separated by t number of years. Both kriging and cokriging were performed on a 1- by 1-m grid; the resulting data were back-transformed into density (seedlings m^{-2}), and contour maps were constructed.

Exploratory data analysis and nonlinear (used to fit semivariogram models) and linear regressions were performed with SAS (1989) software. Empirical variograms were calculated with GS+ software (Anonymous 1994). GSLIB (Deutsch and Journel 1998) was used for the cross-semivariograms, kriging, and cokriging analyses.

Results and Discussion

Of the seven species examined, *S. viridis* occurred most frequently and had the highest mean density across all years compared to other annual weed species (Table 1). *Cirsium arvense* was the most common perennial species. Mean weed densities of all other species varied considerably across years and therefore are not emphasized in the analysis and discussion.

Semivariogram Parameter Analysis

In the field, a directional effect (anisotropy) was evident as elliptical weed patches that were longest in the direction of the crop rows (Figure 1). The total variation (i.e., the sill) was always higher across crop rows (the 90° direction) than along crop rows (0° direction) (Table 2; Figure 2). Conversely, the distance over which weed density data was correlated (range a_1) was greater in the direction of the crop row compared to across the rows. The most likely reason for the difference in ranges (geometric anisotropy) is that weed seeds and other propagules are moved in the direction of crop rows by agricultural tillage and harvesting implements, although other factors, such as water and gravity, may also play a role. A possible explanation for the difference in total variation (zonal anisotropy) would be the variation in performance of field implements (e.g., planter, cultivator, and combine). The differing speeds, depth adjustments, and other factors that occurred during north–south passes of these tools across the field may have contributed to an east–west heterogeneity in weed spatial distribution.

Analysis of the linear model in Equation 8 showed that mean weed density was a significant factor affecting semivariogram model parameters (Table 3). As mean weed density increased, the separation distance at which individual weed density observations were correlated (a_1) increased, suggesting that the size of individual patches increased as mean weed density increased. Moreover, as mean seedling density increased, spatial variability between the two directions (c_2) increased, suggesting a greater tendency toward elliptically shaped weed patches. Year and growth habit effects did not affect semivariogram parameter estimates in Equation 8.

In the linear model in Equation 9, an increase in seed dispersal before harvest resulted in a decrease in spatial variability in the direction of the crop rows (c_1) but increased unexplained variability (nugget) (Table 3). Indeed, the sampling grid used in this work was not fine enough to model

TABLE 2. Parameter values of the semivariogram models describing the spatial structures of weed densities for *Amaranthus retroflexus, Asclepias syriaca, Brassica kaber, Elytrigia repens, Chenopodium album, Cirsium arvense,* and *Setaria viridis* from the Swan Lake Research Farm, 1993 to 1997.

Year	Species	Semivariogram parameters				
		nugget c_0	contribution c_1	contribution c_2	range a_{1_0}	range a_{1_90}
					m	m
1993	*A. retroflexus*	1.75	0.34	0.23	38.3	1.00
	B. kaber	8.67	0.00	0.65		
	E. repens	0.54	0.04	0.13	32.8	0.25
	C. album	0.24	0.50	0.24	11.9	19.6
	C. arvense	0.63	0.69	0.11	19.2	8.69
	S. viridis	0.90	1.51	3.04	39.0	30.1
1994	*A. retroflexus*	0.23	0.33	0.01	12.4	1.00
	A. syriaca	0.11	0.05	2.6×10^{-8}	12.6	1.26
	B. kaber	0.25	7.7×10^{-8}	0.01	37.5	13.6
	C. album	0.00	0.43	0.03	8.83	0.98
	C. arvense	0.98	1.03	0.36	25.8	35.8
	S. viridis	0.93	1.33	1.80	42.7	25.0
1996	*A. retroflexus*	1.31	1.63	0.10	18.5	6.69
	A. syriaca	0.29	0.08	0.003	11.8	0.00
	C. album	0.00	0.53	0.02	10.5	4.5×10^{-6}
	C. arvense	0.43	4.1×10^{-1}	0.01	11.6	11.2
	S. viridis	0.31	2.00	2.40	34.2	10.0
1997	*A. retroflexus*	0.12	0.04	0.02	12.4	1.00
	A. syriaca	0.39	0.13	0.11	11.5	0.97
	E. repens	0.25	0.28	0.63	46.7	1.00
	C. album	0.01	0.07	3.04×10^{-9}	10.0	2.98
	C. arvense	0.37	0.41	1.06×10^{-9}	28.3	7.6×10^{-8}
	S. viridis	0.77	1.42	0.54	30.0	30.0

the effect on patch shape of preharvest seed dispersal (i.e., seeds falling close to their source plants). The simultaneous decrease in the magnitude of spatial variability between directions (c_2) suggests that preharvest seed dispersal is spatially uniform in all directions. This is not surprising in fields planted to small-stature crops like *G. max,* where weed flowers are usually above the crop canopy. Even if seeds were moved slightly further in one direction by wind gusts or animals, these movements probably would have resulted in more random dispersal than from combines and would have contributed little to changes in directional spatial structure. In taller crops like *Zea mays* L. (corn), weed flowers remain primarily below the crop canopy. In such crops, preharvest weed seed dispersal might be less uniform and have more of a directional effect because propagules could move more freely along the open interrow areas than across "wall-like" rows of *Z. mays* stems.

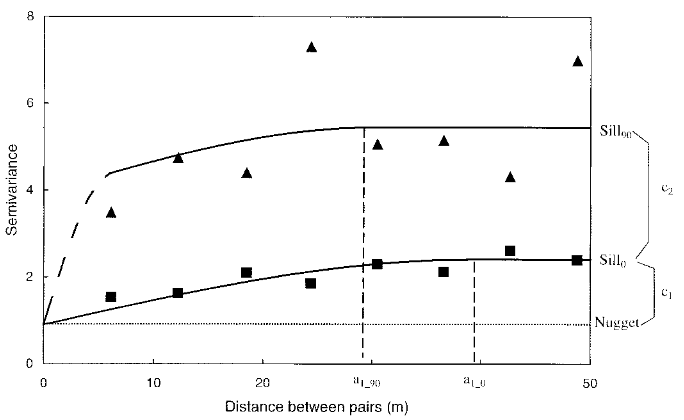

FIGURE 2. Example of empirical semivariogram for directions 0° (■) and 90° (▲) for *Setaria viridis* in 1993 and fitting of a nested spherical model (————) using Equation 4. c_1 is the contribution to the spatial structure of the sill, a_{1_0} and a_{1_90} are the ranges for the 0° and 90° directions of the first spherical model, and c_2 is the contribution of the second spherical model; a_{2_0} is infinite and a_{2_90} is between 0 and the minimum sampling distance, 6.1 m.

An increase in weed seed dispersal during harvest resulted in an increase in spatial variability in the direction of crop rows but had no effect on differences in spatial variability along vs. across rows (Table 3). Moreover, the range parameter tended to decrease as more seed is dispersed during harvest. This decrease is not easily explained but could be the result of an overlap with existing weed patches and greater dispersal distance caused by the combine harvester. Weed densities in the patch intersection would not be correlated to densities in the centers of existing patches.

The effect of plant habit (i.e., the annual or perennial nature of the species) in Equation 10 is consistent with the above-described effects of seed dispersal before and during harvest because the contribution of the main spatial structure is lowest for perennials. In other words, species that produce few seeds dispersed by combine and whose growth is dependent on vegetative propagation will produce offspring that remain close to the parent plant.

Germination rates of fresh seeds (high b_1 values) had a significant effect on the range parameter and on the degree of spatial variability between directions (c_2) (Table 3). Conversely, germination rates of older seeds affected only spatial variability along the crop row (c_1). Germination rate and seedling density do not cause patch shapes and sizes but

TABLE 3. Effect of direction, year, and species characteristics on the parameters of the semivariogram models from the Swan Lake Research Farm, 1993 to 1997.[a,b]

Output variables	Direction effect	Year effect	Mean density	Species characteristics: Growth habit	Seed dispersal: Before harvest	Seed dispersal: During harvest	Germination rates: b_1	Germination rates: b_2
	P value							
Model I (Equation 8)								
$sill_0$/mean	ns	ns	ns	ns	ns	ns	ns	ns
$c_1/sill_0$	ns	ns	ns	ns	ns	ns	ns	ns
$c_2/sill_0$	NA	ns	0.0001 (+)	ns	NA	NA	NA	NA
a_1	0.001	ns	0.002 (+)	ns	NA	NA	NA	NA
Model II (Equation 9)								
$sill_0$/mean	NA	ns	ns	NA	0.04 (+)	ns	NA	NA
$c_1/sill_0$	NA	ns	NA	NA	0.0005 (−)	0.0003 (+)	NA	NA
$c_2/sill_0$	NA	ns	NA	NA	0.04 (−)	ns	NA	NA
a_1	0.006	ns	NA	NA	ns	0.003 (−)	NA	NA
Model III (Equation 10)								
$sill_0$/mean	ns	ns	ns	ns	ns	ns	ns	ns
$c_1/sill_0$	NA	0.07	NA	0.001	NA	NA	ns	0.0001 (+)
$c_2/sill_0$	NA	ns	NA	ns	NA	NA	0.008 (+)	ns
a_1	0.003	ns	NA	ns	NA	NA	0.003 (+)	ns

[a] Abbreviations: ns, not significant at $P > 0.10$ when included in the linear model; NA, effect was not tested for this output variable.
[b] A (+) or (−) means that the explanatory and output variables are positively or negatively correlated, respectively.

favor their expression. For example, high germination rates and seedling densities make it easier to identify patches and analyze spatial structures. The year effect is nearly nonsignificant; most of the differences between years are included in the use of mean seedling density as an explanatory variable.

There are few studies to which these results can be compared. There are a few reports on the spatial distribution of *C. album*. The range values found at Swan Lake (9 to 19 m along rows; 1 to 11 m across rows) are similar to those reported by Halstead et al. (1990), Cardina et al. (1995, 1996). However, these authors did not observe anisotropy for these species. In contrast, Johnson et al. (1996) reported larger range values along crop rows. Their study showed larger ranges across rows, and total variation (sill) was highest in the direction of crop rows. However, cropping conditions were not the same in the two studies: the field examined by Johnson et al. (1996) was a ridge-tilled *Z. mays*/*G. max* rotation in Nebraska. Furthermore, the latter field was sampled entirely, in contrast to the former field, where only the central portion was studied and the often-important variation next to field margins was neglected. At Swan Lake, for instance, *S. viridis* and *C. arvense* densities were often higher at the margins. This density increase could be due to seed immigration, lower levels of crop establishment, or poorer weed control in these areas.

Cross-Semivariogram Parameter Analysis

For those weed species that occurred in high densities and had cross-semivariograms not limited to a nugget effect (nugget effect = no spatial structure), the sills were highest across crop rows (90° direction). For all other species, the direction with the highest spatial variation was along rows (0° direction). The range values were also generally lower for cross-semivariograms (mean range: 11 m) compared to the semivariograms (mean: 16 m).

Patch persistence over time (as described by the weed density correlation values for distance $h = 0$ across years) was negatively affected by seed dispersal characteristics, regardless of whether seed was dispersed before or after harvest. In general, patch persistence was greater for perennial (low dispersal rate) compared to annual (high dispersal rate) weed species. This is consistent with Gerhards et al. (1997), who reported higher patch persistence for perennials. Conversely, Wilson and Brain (1990) reported that *Alopecurus myosuroides* Huds. (blackgrass), an annual weed species with high seed production, was spatially stable. They attributed this to a lack of colonization in new locations when effective herbicides were applied. Therefore, patch persistence is most likely the result of dispersal rate, dispersal distance, and ability of a weed species to colonize. Preharvest seed dispersal increased spatial variability in the direction of the crop rows (c_1) and the sill difference between the directions (c_2), whereas seed dispersal during harvest decreased spatial variability in the direction of crop rows (Table 4). The relationships between weed densities and locations of two successive years described by the cross-semivariograms, therefore, were of a different nature than those resulting in the weed patches described by the semivariograms. Indeed, the cross-semivariograms can describe only the patch locations across time (movement) related to purported preharvest seed dispersal (i.e., seeds falling next to the seed-producing plants). In contrast, seeds dispersed by harvest combines may have moved too far to trace relationships to their original locations. There must be some subsequent effect of cultural practices on seed locations because the ranges showed a marked anisotropy, with higher ranges in the direction of the *G. max* rows (Table 4). The field was not plowed, but seeds still could be moved by planting implements, tractor tires, interrow cultivators, and so on. The lower range values of the cross-semivariograms might also be explained by the different underlying mechanisms. The ranges of the semivariograms have been related to seed dispersal by harvest equipment, and the resulting patches were, therefore, larger than the distance separating shed seeds from the mother plant, which is illustrated by the cross-semivariogram.

High germination rates for younger seeds (high b_1 values) increased spatial variability in the direction of the crop rows (c_1), increased the difference in variability between the directions (c_2), and increased the spatial correlation distance along rows (a_1). This may be the result of a high proportion of seeds in year i producing seedling in year $i + 1$. Design of sampling plans based on plant spatial distribution during the previous year should be easier for species with low-dormancy seeds compared to other species with higher levels of dormancy.

There was no year effect on any output variable, probably because the year effect was integrated into the seedling density variables of years i and $i + 1$. High seedling densities for year i increased patch persistence over years, difference in variability for the two major directions (c_2), and the ranges of the along-row spatial structure (a_1) of the cross-semivariograms (Table 4). As for the semivariograms, these density effects are probably not so much the causes of patch shapes and sizes but represent the influence of higher densities and nonzero counts on the statistical power of the analysis.

Weed Mapping

Because weeds are assumed to be homogeneously distributed across a field, spray/no-spray decisions typically are based on mean density (or perceived weed pressure) and applied uniformly throughout the field. However in most cases, weeds are heterogeneously distributed, suggesting that weed control could be improved if herbicide application was based on the location of weed patches (Cardina et al. 1995, 1996; Johnson et al. 1995) (Figure 1).

Precision agriculture requires either (1) expensive equipment to recognize, quantify, and construct binary spray/no-spray actions or (2) time- and labor-consuming field sampling to obtain data for producing maps used to direct the sprayer. In the case of preemergence herbicide applications, no visual information (i.e., seedling densities) would be available in the field at the time when herbicides are applied. In this situation, it would be helpful if the spatial distribution of weeds from one year could be used as a basis for making spraying decisions the following year. One possibility would be to predict seedling distributions using seedbank data (Cardina et al. 1996), but seedbank sampling is time-consuming, especially if high precision is required (Dessaint et al. 1990; Goyeau and Fablet 1982; Wiles et al. 1996). Another alternative would be to assume that a weed map developed in one year provides useful spatial information for the following year.

Table 4. Effect of direction, year, and species characteristics on the parameters of the cross-semivariogram models from the Swan Lake Research Farm, 1993 to 1997.[a,b]

Output variables	Direction effect	Year effect	Mean density		Species characteristics				
					Growth habit	Seed dispersal		Germination rates	
			year i	year $i-1$		Before harvest	During harvest	b_1	b_2
	P value								
Model I (Equation 8)									
ρ_0	NA	ns	0.001 (+)	ns	0.15	NA	NA	NA	NA
c_1/sill_0	NA	ns	ns	ns	0.09	NA	NA	NA	NA
c_2/sill_0	NA	ns	0.0001 (+)	0.004 (−)	0.11	NA	NA	NA	NA
a_1	0.02	ns	0.04 (+)	ns	NA	NA	NA	NA	NA
Model II (Equation 9)									
ρ_0	NA	ns	NA	NA	NA	0.02 (−)	0.09 (−)	NA	NA
c_1/sill_0	NA	ns	NA	NA	NA	0.07 (+)	0.01 (−)	NA	NA
c_2/sill_0	ns	ns	ns	ns	ns	ns	ns	ns	ns
a_1	0.03	ns	NA	NA	NA	ns	0.13 (−)	NA	NA
Model III (Equation 10)									
ρ_0	NA	ns	NA	NA	0.03	NA	NA	0.01 (+)	0.09 (+)
c_1/sill_0	NA	ns	NA	NA	0.0001	NA	NA	0.03 (+)	ns
c_2/sill_0	NA	ns	NA	NA	ns	NA	NA	0.005 (+)	ns
a_1	0.05	0.14	NA	NA	0.09	NA	NA	0.08 (+)	ns

[a] Abbreviations: NA, effect was not tested for this output variable; ns, not significant at $P > 0.10$ when included in the linear model.
[b] A (+) or (−) means that the explanatory and output variables are positively or negatively correlated, respectively.

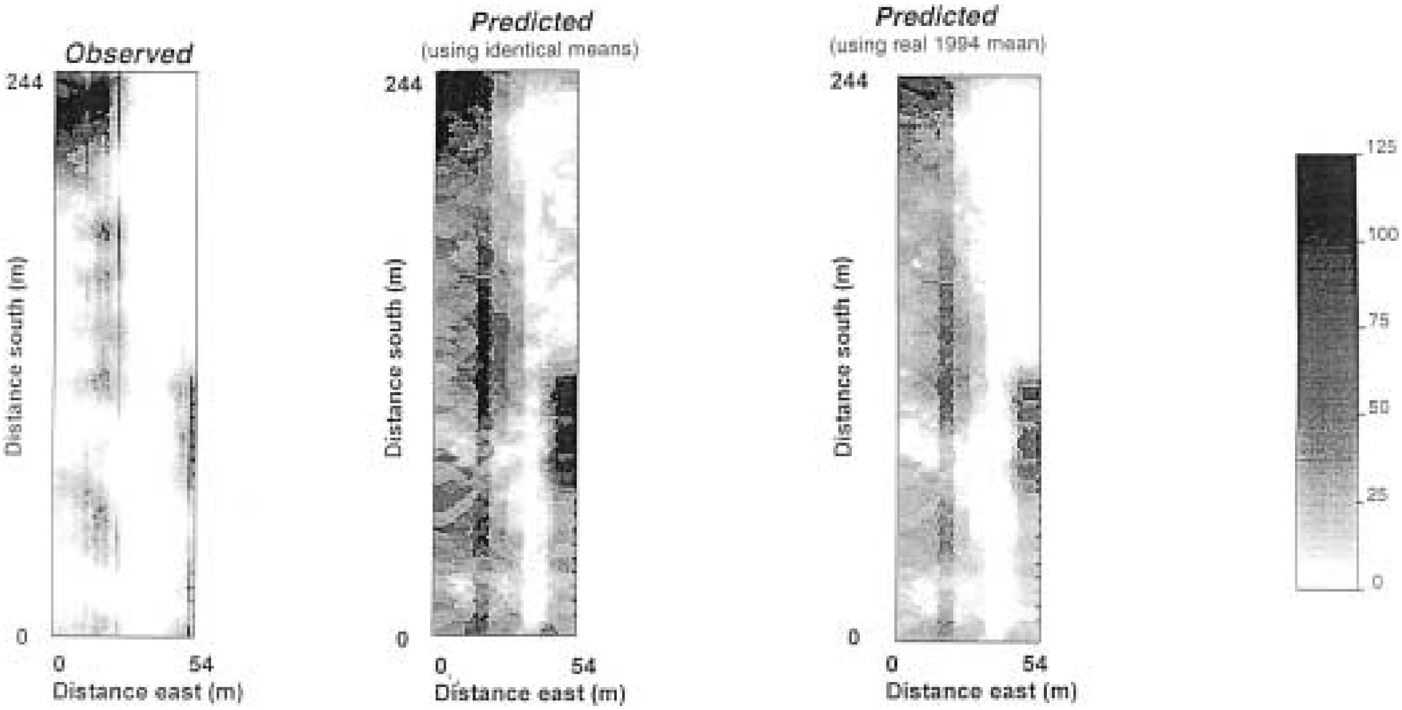

FIGURE 3. Maps of *Setaria viridis* seedling densities for 1994 at the Swan Lake Research Farm. (A) Kriged from the data sampled in 1994. (B) Predicted (cokriged) from the data sampled in 1993, assuming that 1994 mean density is equal to the 1993 mean. (C) Predicted (cokriged) from the data sampled in 1993, using real 1994 mean density. Scale is in plants m^{-2}, with the highest values > 125 plants m^{-2}.

Figure 3 shows the predicted *S. viridis* maps for 1994 based on data from 1993, the semivariograms for both years (1993 and 1994), and a mean cross-semivariogram. If mean weed density in 1994 is assumed identical to that of 1993, the map adequately predicts the location of the seedling patches but overestimates actual density. Nevertheless, if spraying is based on the predicted 1994 weed map, herbicide application could be significantly reduced compared to application decisions based solely on mean weed density. If, for instance, only those areas with more than 27 plants m^{-2} (density threshold for which yield loss equals the price of glyphosate application) were to be sprayed, the use of the 1994 map, based on 1993 samples assuming the same mean density, would lead to the treatment of 40% of the field. Use of the map kriged from the 1994 samples would only result in the spraying of 12% of the field (Table 5). This discrepancy (error) consists almost entirely of areas that are unnecessarily sprayed (Table 5; Figures 3A and 3B). Therefore, the use of weed maps cokriged with the previous year's samples does not result in any supplementary yield loss. If the mean density for 1994 could be projected by population dynamics models (e.g., Gonzalez-Andujar and Perry 1995), for example, the accuracy of the 1994 weed maps could be improved substantially (Figure 3C). In the latter case, the locations of the patches, as well as the actual densities, are predicted more or less correctly. Moreover, the areas to be treated are better estimated as the proportion of unnecessarily sprayed areas decrease (Table 5; Figures 3A and 3C). Analysis of the 1996 to 1997 data lead to the same conclusion: the patches are always correctly located, but the actual

TABLE 5. Prediction errors for spatial herbicide applications based on *Setaria viridis* seedling maps cokriged from data sampled in 1993 at Swan Lake Research Farm. Units are only sprayed if their *S. viridis* density exceeds the chosen threshold value.[a]

Prediction method	Threshold density[b]	Correct prediction (%) — Herbicide treatment: Yes ov > th sv > th	Correct prediction (%) — Herbicide treatment: No ov ≤ th sv ≤ th	Correct prediction (%) — Total	Error (%) — Herbicide treatment: Lacking ov > th sv ≤ th	Error (%) — Herbicide treatment: Unnecessary ov ≤ th sv > th	Error (%) — Total
	plants m^{-2}	%					
Cokriging	27	12	59	71	< 1	28	29
	60	5	83	88	< 1	11	12
Cokriging +	27	8	82	90	5	5	10
1994 mean	60	3	92	95	3	2	5

[a] Abbreviations: ov, observed value (in this case, value for 1994 kriged from 1994 samples); sv, simulated value (in this case, value for 1994 cokriged from 1993 values); th, weed density threshold.
[b] Weed density leading to a yield loss equivalent to the price of herbicide spraying (imazethapyr or glyphosate).

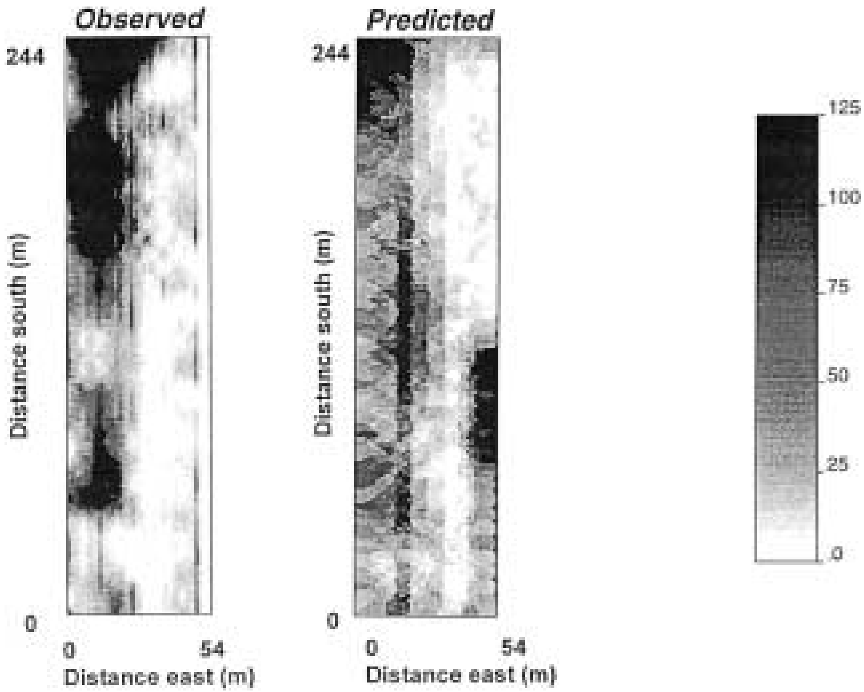

FIGURE 4. Maps of *Setaria viridis* seedling densities for 1996 at the Swan Lake Research Farm. (A) Kriged from the data sampled in 1996. (B) Predicted (cokriged) from the data sampled in 1993, assuming that 1996 mean density is equal to the 1993 mean. Scale is in plants m^{-2}, with the highest values > 125 plants m^{-2}.

density is either overestimated (if the density of the sampled year is higher than that of the predicted year) or underestimated (the opposite case).

The accuracy of the prediction decreases with the number of years between sampling and prediction. The comparison of the predicted (cokriged from the 1993 data and cross-semivariograms) and the observed (kriged) maps for *Setaria* spp. in 1996 (Figure 4) and 1997 (Figure 5) shows that even the location of the patches was predicted with decreasing reliability as the number of years increased between times of sampling (e.g., 1993) and prediction (e.g., 1996 or 1997). In fact, the correlation decreased toward zero between densities in year i and $i + t$ (for distance $h = 0$), with the number of years, t, between sampling and predic-

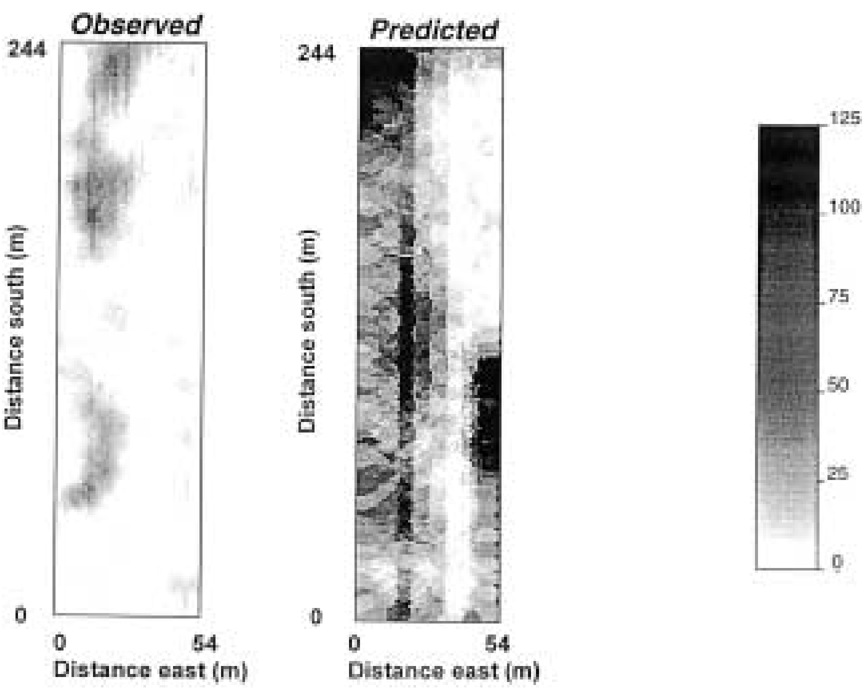

FIGURE 5. Maps of *Setaria viridis* seedling densities for 1997 at the Swan Lake Research Farm. (A) Kriged from the data sampled in 1997. (B) Predicted (cokriged) from the data sampled in 1993, assuming that 1997 mean density is equal to the 1993 mean. Scale is in plants m^{-2}, with the highest values > 125 plants m^{-2}.

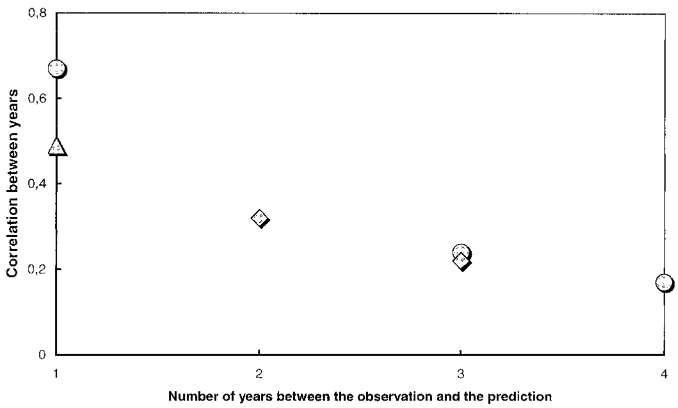

FIGURE 6. Correlation between the *Setaria viridis* densities of year i and year $i + t$ for distance $h = 0$ (●: year $i = 1993$; ♦: year $i = 1994$; ▲: year $i = 1996$).

tion (Figure 6). Although the correlation between distant years was low, the correlation for 1-yr lags was rather high (Figure 6).

Spatial relationships between years should be investigated in fields with more diverse management variables, especially soil tillage, which provides more opportunities for seed movement. Predictions between years could be improved by sampling on a finer grid. In this study, a minimum sampling distance of 6 m is too large to describe small-scale movements such as natural seed shed. However, the most important large-scale component of seed movement (i.e., dispersal by harvest combines) was included. This study also showed that satisfactory prediction of spatial weed distribution was possible over 1 yr without any prior knowledge of the mean density or spatial structure of the next year's weed population. Accordingly, amounts of applied herbicides could be reduced and better adapted to actual weed density, even for preemergence herbicides. Prior knowledge of seedling distributions might also help to improve estimation of weed populations, without having to sample the whole field extensively. This could occur if the approximate location of the patches is known in advance, allowing sampling efforts to be concentrated in those areas, while only sparse surveying would be necessary in areas that are predicted to be weed free.

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Literature Cited

Anonymous. 1994. GS+: Geostatistics for the Environmental Sciences. Version 2.3. Plainwell, MI: Gamma Design Software. 44 p.

Auld, B. A., and C. A. Tisdell. 1987. Economic threshold and response to uncertainty in weed control. Agric. Syst. 25:219–227.

Auld, B. A., and C. A. Tisdell. 1988. Influence of spatial distribution of weeds on crop yield loss. Plant Prot. Q. 31:81.

Bigwood, D. W., and D. W. Inouye. 1988. Spatial pattern analysis of seed banks: an improved method and optimized sampling. Ecology 69: 497–507.

Brain, P., and R. Cousens. 1990. The effect of weed distribution on prediction of yield loss. J. Appl. Ecol. 27:735–742.

Burnside, O. C., R. G. Wilson, S. Weisberg, and K. G. Hubbard. 1996. Seed longevity of 41 weed species buried 17 years in eastern and western Nebraska. Weed Sci. 44:74–86.

Cardina, J., D. H. Sparrow, and E. L. McCoy. 1995. Analysis of spatial distribution of common lambsquarters (*Chenopodium album*) in no-till soybean (*Glycine max*). Weed Sci. 43:258–268.

Cardina, J., D. H. Sparrow, and E. L. Mccoy. 1996. Spatial relationships between seedbank and seedling populations of common lambsquarters (*Chenopodium album*) and annual grasses. Weed Sci. 44:298–308.

Cressie, N. 1991. Statistics for spatial data. New York: J. Wiley. p. 70.

Dent, J. B., R. H. Fawcett, and P. K. Thornton. 1989. Economics of crop protection in Europe with reference to weed control. Proc. Br. Crop Prot. Conf.—Weeds 1989:917–926.

Dessaint, F., G. Barralis, E. Beuret, M. L. Caixinhas, B. J. Post, and G. Zanin. 1990. Étude coopérative EWRS: la détermination du stock semencier. I. Recherche d'une relation entre la moyenne et la variance d'échantillonnage. Weed Res. 30:421–429.

Deutsch, C. V., and A. G. Journel. 1998. GSLIB: Geostatistical Software Library and User's Guide. New York: Oxford University Press. 369 p.

Doyle, C. J. 1991. Mathematical models in weed management. Crop Prot. 10:432–444.

Forcella, F., D. H. Peterson, and J. C. Barbour. 1996. Timing and measurement of weed seed shed in corn (*Zea mays*). Weed Technol. 10: 535–543.

Gerhards, R., M. Sökefeld, D. Knuf, and W. Kühbauch. 1996. Kartierung und geostatistische Analyse der Unkrautverteilung in Zuckerrübenschlägen als Grundlage für eine teilschlagspezifische Bekämpfung. J. Agron. Crop Sci. 176:259–266.

Gerhards, R., D. Y. Wyse-Pester, D. Mortensen, and G. A. Johnson. 1997. Characterizing spatial stability of weed populations using interpolated maps. Weed Sci. 45:109–119.

Ghersa, C. M., and M. L. Roush. 1993. Searching for solutions to weed problems. Do we study competition or dispersion?. BioScience 43: 104–109.

Gonzalez-Andujar, J. L. and J. N. Perry. 1995. Models for the herbicidal control of the seedbank of *Avena sterilis*: the effects of spatial and temporal variability. J. Appl. Ecol. 32:578–587.

Goyeau, H., and G. Fablet. 1982. Etude du stock semencier de mauvaises herbes dans le sol: le problème de l'échantillonnage. Agronomie 2: 542–551.

Halstead, S. J., K. L. Gross, and K. A. Renner, 1990. Geostatistical analysis of the weed seed bank. Proc. North Cent. Weed Sci. Soc. 45:123–124.

Hamlett, J. M., R. Horton, and N.A.C. Cressie. 1986. Resistant and exploratory techiques for use in semivariogram analyses. Soil Sci. Soc. Am. J. 50:868–875.

Hughes, G. 1990. The problem of weed patchiness. Weed Res. 30:223–224.

Johnson, G. A., D. A. Mortensen, and C. A. Gotway. 1996. Spatial and temporal analysis of weed seedling populations using geostatistics. Weed Sci. 44:704–710.

Johnson, G. A., D. A. Mortensen, and A. R. Martin. 1995. A simulation of herbicide use based on weed spatial distribution. Weed Res. 35: 197–205.

Journel, A. G. and C. Huijbregts. 1978. Mining Geostatistics. New York: Academic Press. p. 194.

Kareiva, P. 1990. Population dynamics in spatially complex environments: theory and data. Philos. Trans. R. Soc., London B 330:175–190.

Legendre, P., and M. J. Fortin. 1989. Spatial pattern and ecological analysis. Vegetatio 80:107–138.

Lloyd, M. L. 1967. Mean crowding. J. Anim. Ecol. 36:1–30.

Ludwig, J. A. and J. R. Reynolds. 1988. Spatial pattern analysis. Pages 13–66 *in* J. A. Ludwig and J. R. Reynolds, eds. Statistical Ecology: A Primer on Methods and Computing. New York: J. Wiley.

Lybecker, D. W., E. E. Schweizer, and R. P. King. 1991. Weed management decisions in corm based on bioeconomic modeling. Weed Sci. 39:124–129.

Marshal, E.J.P. 1988. Field-scale estimates of grass weed populations in arable land. Weed Res. 28:191–198.

Maxwell, B. D. and C. Ghersa. 1992. The influence of weed seed dispersion versus the effect of competition on crop yield. Weed Technol. 6:196–204.

Moloney, K. A. 1988. Fine-scale spatial and temporal variation in the demograph of a pernennial bunchgrass. Ecology 69:1588–1598.

Mortensen, D. A., G. A. Johnson, and L. J. Young. 1993. Weed distribution in agricultural fields. Pages 113–124 *in* P. C. Robert, R. H. Rust, and W. E. Larson, eds. Soil Specific Crop Management. Madison, WI: American Society of Agronomy.

Nordmeyer, H. and P. Niemann. 1992. Möglichkeiten der gezielten Teilflächenbehandlung mit Herbiziden auf der Grundlage von Unkrautverteilung und Bodenvariabilität. Z. Pflkrankh. Pflschutz Sonderheft 13:539–547.

[SAS] Statistical Analysis Systems. 1989. SAS/STAT User's Guide. Version 6. Cary, NC: Statistical Analysis Systems Institute. 1028 p.

Streibig, J. C., A. Gottschau, B. Dennis, H. Haas, and P. Polgaard. 1984. Soil properties affecting weed distribution. 7th Int. Symp. Weed Biol. Ecol. Syst. 7:147–154.

Thompson, K. 1986. Small-scale heterogeneity in the seed bank of an acidic grassland. J. Ecol. 74:733–738.

Thornton, P. K., R. H. Fawcett, J. B. Dent, and T. J. Perkins. 1990. Spatial weed distribution and economic thresholds for weed control. Crop Prot. 9:337–342.

Van Groenendael, J. M. 1988. Patchy distribution of weeds and some implications for modelling population dynamics: a short literature review. Weed Res. 28:437–441.

Wiles, L. J., D. H. Barlin, E. E. Schweizer, H. R. Duke, and D. E. Whitt. 1996. A new soil sampler and elutriator for collecting and extracting weed seeds from soil. Weed Technol. 10:35–41.

Wiles, L. J., H. J. Gold, and G. G. Wilkerson. 1993. Modelling the uncertainty of weed density estimates to improve post-emergence herbicide control decisions. Weed Res. 33:241–252.

Wiles, L. J., G. W. Oliver, A. C. York, H. J. Gold, and G. G. Wilkerson. 1992a. Spatial distribution of broadleaf weeds in North Carolina soybean (*Glycine max*) fields. Weed Sci. 40:554–557.

Wiles, L. J., G. G. Wilkerson, H. J. Gold, and H. D. Coble. 1992b. Modeling weed distribution for improved postemergence control decisions. Weed Sci. 40:546–553.

Wilson, B. J. and P. Brain. 1990. Weed monitoring on a whole farm-patchiness and the stability of distribiton of *Alopecurus myosuroides* over a ten-year period. Pages 45–52 *in* Integrated Weed Management in Cereals. Proceedings of the EWRS Symposium, Helsinki. Wageningen, The Netherlands: EWRS.

Wilson, R. G., E. D. Kerr, and L. A. Nelson. 1985. Potential for using weed seed content in the soil to predict future weed problems. Weed Sci. 33:171–175.

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Glossary

Anisotropy: is present when spatial autocorrelation of a process changes with direction.

Anisotropy (geometric): occurs when the range of the semivariogram changes with direction while the sill remains constant.

Anisotropy (zonal): occurs when the sill of the semivariogram changes with direction while the range remains constant.

Autocorrelation: $\rho_h = (1 - \gamma_h)/(\sigma \cdot \sigma')$, where ρ_h is autocorrelation and γ_h is the empirical semivariance for distance h, σ_j and σ_{j+t} are the standard deviations of variables z_i and z_i', *respectively.*

Cokriging: estimates a sparsely sampled variable, z', using the sampled data of this same variable and that of an extensively sampled variable, z, as well as the semivariograms of the variables z and z' and their cross-semivariogram.

Contribution: is the difference between sill and nugget (if any).

Cross-semivariogram (empirical): is $\gamma_h = (1/(2 \cdot N_h)) \; \Sigma \; (z_{i+h} - z_i)(z'_{i+h} - z'_i)$, where γ_h is the empirical cross-semivariance for the distance h, N_h is the number of points separated by the distance h, and z_i and z_i' are the data values of two variables measured at location i.

Kriging: is the linear interpolation method that allows estimation of variable z_i at unsampled locations using a weighted linear combination of available samples and a modeled semivariogram.

Nugget: represents the microscale variation that cannot be described with the sampling plan used or measurement error.

Range: is the distance (if any) at which data are no longer autocorrelated.

Semivariance (empirical): is $\gamma_h = (1/(2 \cdot N_h)) \; \Sigma \; (z_{i+h} - z_i)^2$, where γ_h is the empirical semivariance for the distance h, N_h is the number of points separated by the distance h, and z_i is a data value measured at location i. The semivariogram provides a description of how the data are related (correlated) with distance.

Sill: is the value of semivariance γ_h for distance larger than range.